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Scaling agroforestry land suitability analysis in Odisha, India: a machine learning approach

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Agroforestry practices are one of the major pillars of Natural Resources Management (NRM), offering substantial benefits by improving environmental conditions, socio-economy, soil health, biodiversity, and climate resilience. Despite multi-dimensional benefits, robust data for regional planning and effective implementation are lacking, particularly in combined with existing land management practices. Further, analyses are often conducted using a set of reference datasets without validating the scalability. This study aimed to address this gap by leveraging a pre-trained machine learning (ML)-based Multi-Criteria Evaluation (MCE) model to assess agroforestry land suitability in Odisha, India, and validating the outcome with reference data from an independent region. Multi-temporal Sentinel-2 data were used to generate Land Use Land Cover (LULC) and cropping intensity maps, where Random Forest (RF) achieved above 94% classification accuracy, outperforming Support Vector Machine (SVM; above 93%). In comparison to traditional expert-defined weights, RF model-derived variable importance was integrated with fuzzy-MCE approach for agroforestry site suitability analysis. A diverse data array, such as topography, soil parameters, climate conditions, and socioeconomic factors, were employed, wherein the proximity variables contributed ~70% of total weight. Independent validation using field data from another region with similar agricultural practices and socio-economic characteristics showed high mean suitability (>0.87; range 0.71–0.95). Moreover, the generated Receiver Operating Characteristic (ROC) analysis indicated an Area Under the Curve (AUC) of 0.89, exhibits strong model performance and high capability to site suitable agroforestry sites. Intervention-specific analysis indicated that >94% of double- and single-cropped lands, ~96% of settlement areas, and >90% of permanent fallow and wastelands were found highly suitable for (i) bund and boundary plantations and intercropping, (ii) home gardens, and (iii) block/bulk plantation agroforestry practices, respectively. Further, we deployed the site suitability layer through a web platform. The developed WebGIS portal

enables open data access, spatial querying and intervention planning, providing a practical decision-support tool for state-level agroforestry planning and implementation.

KEYWORDS

agroforestry, fuzzy-MCE (multi-criteria evaluation), machine learning (ML), Odisha, random forest (RF), WebGIS

1 Introduction

In India, the imperative to sustain a rapidly growing population on finite land resources has intensified the conflict between immediate agricultural productivity and long-term ecological stability. While intensive monocropping addresses short-term food security and economic returns, it has precipitated widespread soil degradation, groundwater depletion, and biodiversity loss (Jose, 2009; Torralba et al., 2016). The periodic forest land conversion from forest to non-forest categories has deteriorated the ecosystem and modified the energy and water balance (Behera et al., 2018a; Das et al., 2018). Agroforestry, the integration of woody perennials with crops, offers a viable solution to these challenges by restoring soil health (Jose et al., 2004), increasing biodiversity (Tscharntke et al., 2005), improving resilience to climate change (Verchot et al., 2000), and increasing crop yields and nutrition security (Schroth et al., 2004). This sustainable land use practice not only contributes to ecological balance, but also supports livelihoods and diversify farmers income, making it a critical component of modern agricultural systems. Agroforestry also plays a significant role in sequestering the carbon and achieving India's Nationally Determined Contribution (NDC) targets (Nath et al., 2021; Dhyani et al., 2020; Singh et al., 2024). Studies have shown that agriculture-based economy are susceptible to extreme weather events, wherein agroforestry is more resilient in nature (Mourya and Mehta, 2021). As a middle-income country, India has pledged to expand the area under agroforestry to 50 Mha by the end of 2050, restoring pastures, groves, fallows, and cultivable fallows, and rehabilitating soils (Dhyani, 2014). The recent National Agroforestry Policy (NAP, 2014) was introduced for dedicated promotion of agroforestry interventions in India, wherein the Green India Mission (GIM) endorses agroforestry interventions in rural regions. In addition, the Rashtriya Krishi Vikas Yojana (RKVY) provides financial incentives for nursery development and boundary/block plantations), Mission for Integrated Development of Horticulture (MIDH) supports holistic growth of horticulture, including bamboo), and Greening and Restoration of Wasteland with Agroforestry (GROW) (by NITI Aayog) aims to restore degraded lands through agroforestry. Multiple government initiatives have been taken in India, which promote natural resources management (NRM), including agroforestry practices, through rural participatory-based approaches. The convergence of the Sub-Mission on Agroforestry (SMAF) and the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) significantly contributes to agroforestry interventions, where the MGNREGA provide funding for the plantation and maintenance work. Recently, according to the Department of Public Relations, Government of Madhya Pradesh (2025), the Government of Madhya Pradesh, India, has initiated a novel program named “Ek

Bagiya Maa Ke Naam”, focusing on women's empowerment through agroforestry interventions in the state. Such initiatives not only promote sustainable NRM, but also generate massive rural livelihoods, income, and employment in India.

While several government and non-government programs have been initiated, robust data is required for planning and ground implementation (Behera et al., 2018b). Despite its apparent advantages of agroforestry and national initiatives, the implementation of agroforestry interventions faces challenges, primarily concerning land suitability and compatibility with current farming practices (Degu et al., 2010). The use of Geographic Information System (GIS) analysis has proven effective in site suitability identification. Such approaches integrate remote sensing data (satellite and drone surveys) and derived spatial layers, and diverse data on climate (temperature and precipitation), soil (type, nutrient, and moisture), topography (elevation, slope, and aspect), and socioeconomic factors (Talukdar et al., 2020). Previous studies have applied GIS-aided Multi-Criteria Decision Analysis (MCDA) or Multi-Criteria Decision Making (MCDM) or Multi-Criteria Evaluation (MCE) techniques to demonstrate their ability to incorporate multiple variables into the analysis (Dağıstanlı et al., 2018; Everest et al., 2021; Memarbashi et al., 2017). Ahmad et al. (2017) used the FAO guidelines to assess agroforestry suitability in Jharkhand, India, wherein they employed various parameters such as climate, topography, and soil nutrient availability, and predicted agroforestry suitability in more 32% of the total geographical area. Nath et al. (2021) applied MCE on 19 variables (climate, topography, soil, ecological, and socio-economic) for agroforestry suitability analysis in the northeast Indian states and reported that around 90% of the land has good potential. Variable selection and weight estimation are essential components of site suitability assessment. Several techniques have been tested in weight estimation, starting from a pair-wise comparison matrix to the parametric method (Acharya et al., 2019), ordered weighted mean (Singh et al., 2021a), and membership approach (Chuma et al., 2021). Past studies have also tested regression-based and principal component analysis (PCA) for factors weight estimation (Elsheikh et al., 2013). Recent studies demonstrate a clear shift from traditional GIS-based weighted overlays toward hybrid and artificial intelligence (AI)-enabled suitability modeling. A few studies have used machine learning (ML) models for site-specific suitability assessment (Feng et al., 2018; Komolafe et al., 2019). Agrawal and Gupta (2017) integrated AHP-based spatial MCE with ML in a semi-arid ecosystem, and reported that ML-enhanced land suitability classification and enabled automated crop recommendations compared to conventional overlay methods. The potential of ML models to revolutionise agroforestry interventions is significant, with algorithms such as Random Forest (RF) showing promising results in site suitability analysis

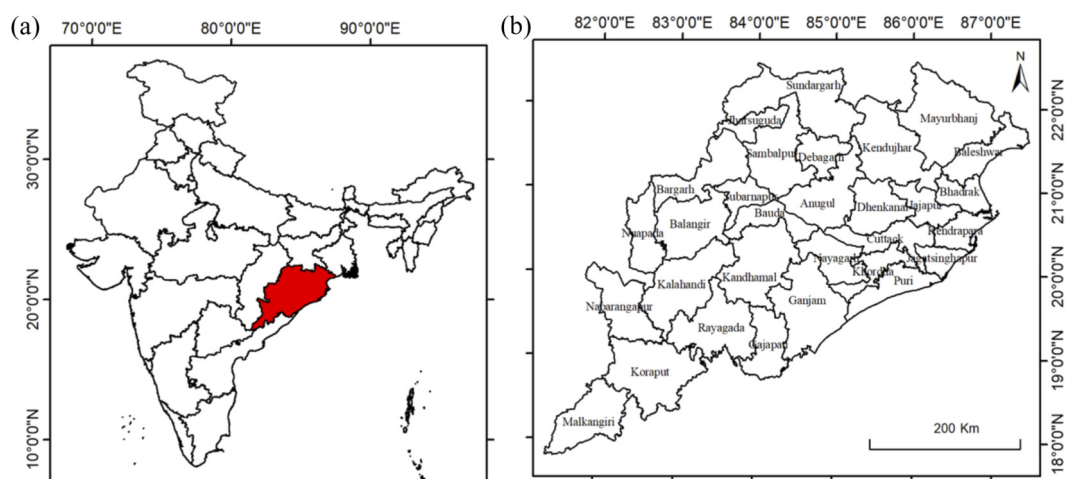


FIGURE 1
Study area map of (a) Odisha state in India and (b) District map of Odisha.

owing to their robustness, high accuracy, and low sensitivity to parameter optimisation (Singh et al., 2022). However, despite the application of various ML models in site suitability analysis, exploration of these advanced techniques, particularly in the context of agroforestry suitability in India, remains relatively nascent (Chen et al., 2019; Shi et al., 2022).

The integrated Web-based platforms and GIS tools, called WebGIS, enable geospatial data management using a web browser (Baker, 2015). It has the capabilities to create, process, and store the data using cloud servers, which are then used for interactive visualization, query, analysis, and sharing. Additionally, the graphical user interface (GUI) allow interactive and smooth data processing, and particularly useful for non-programmer data analysts. Developing WebGIS or GUI tools enable the execution of multiple algorithms with the slightest programming, mathematical and statistical knowledge, and bridges the gap between new model users and expert model developers (Nielsen et al., 2017). Various open source and commercial data processing and programming platforms such as Quantum-GIS (QGIS), ArcGIS, R, Matlab, Python, etc., allow developing interactive user-defined GUI. Using the QGIS platform, Nielsen et al. (2017) developed the Water Ecosystem Tool (WET) for assessing the aquatic ecosystem, which integrated the Soil and Water Assessment Tool (SWAT) to simulate the effects of land use change on marine ecosystems. The Shiny package in the R programming platform enables developing such interactive tools, which support geospatial and statistical data analysis, and data visualization (Moraga, 2017). Aekakkarakarunroj et al. (2020) developed a reservoir mapping tool based on dam point location and digital elevation model through the ArcGIS Desktop 10.5 Model Builder on a publicly available web interface. The WebGIS server, such as a GeoServer, manages Open Geospatial Consortium (OGC) services requests such as Web Map Services (WMS) and Web Feature Services (WFS). GeoServer is an open-source server that enables in geospatial data edit and interoperability, i.e., data exchange utilizing open standards. Data is made available using standard interfaces such as WMS, WFS, Web Coverage Services

(WCS), and Web Processing Service (WPS). Mudi et al. (2021) developed a WebGIS application for biodiversity data hosting and collection using citizen-science. They used a client server-based architecture that included hypertext markup language (HTML), CSS, and PHP for presentation tire; leaflet JavaScript library for application logic; and phpMyAdmin and MySQL for database storing and management. The developed application hosts spatial data, and users can upload ground data with geolocation and field photos.

The adoption of advanced algorithms for agroforestry in India's diverse landscapes has not been extensively studied, and the suitability and effectiveness of ML approaches remain underexplored. This study involves a comprehensive analysis that spans both qualitative and quantitative datasets (Nguyen et al., 2015), including farmers' perspectives to provide a grounded approach (Jamil et al., 2018). Further, a non-parametric method was applied, coupled with statistical analysis to provide a more empirical understanding (De La Rosa and Van Diepen, 2002). This study aimed to fill the existing gap by applying ML to assess land suitability for agroforestry interventions. Moreover, studies on establishing the transferability of agroforestry models in comparable zones are limited. The study tested the applicability of ML-derived weight values for agroforestry site suitability analysis in a past study based on field observations from a similar landscape in the region. Through this, the study aims to provide an accurate and scalable methodology for agroforestry suitability analysis and intervention planning, leveraging the rich available datasets in eastern India.

2 Study area

This research focused on the Odisha state of India, situated between 81° 24' and 87° 29'E longitude and 17° 48' and 22° 34'N latitude, covering an extensive area of 1,55,707 km² (Figure 1). Positioned between the Tropic of Cancer, Odisha experiences a tropical climate with elevated temperatures and moderate

TABLE 1 List of variables used in the study for agroforestry suitability mapping.

Criteria	Variables	Unit	Agroforestry classes/fuzzy scale for continuous data				Data sources
			Very High	High	Moderate	Low	
Soil	Soil type	Code	Fine loamy, clayey	Fine mixed	Course loamy, sandy loam	Clay sandy, sandy	NBSS & LUP
	Depth		Mod deep	Mod shallow	Shallow	-	
	Texture		Fine	Fine to course	Course	-	
	Soil drainage		Very well	Well	Mod well	-	
	pH	-log(H ⁺)	6.5–7.5	5.5–6.5	7.5–8.5	-	
Topography	Slope	Degree	Sigmoidal decreasing				ALOS PALSAR
Climate	Annual mean temperature	°C	Monotonically increasing linear				Worldclim
	Annual min. temperature						
	Annual max. temperature						
	Rainfall	Mm	Sigmoidal increasing				CHIRPS
Socioeconomic	Distance from forest	meter	Monotonically decreasing linear				LULC
	Distance from settlement						
	Distance from waterbody						
	Distance from cropland						
	Distance from road						ORSAC

Odisha Space Application Center (ORSAC).

precipitation (Mohanta et al., 2018). The state encounters high temperatures during the summer, with the highest reaching 44 °C, while the minimum temperatures may drop below 4 °C in winter. The average temperature varies from 20.17 °C to 28.27 °C (Supplementary Figures S2a–c). The state primarily relies on the Southwest and Northwest monsoons for precipitation. Odisha experiences an average annual precipitation of 1,482 mm, with variations ranging from 1,146 mm to 2054 mm in different regions (Supplementary Figures S3d). Odisha is heavily dependent on monsoonal precipitation and lacks a robust irrigation system during dry periods. The agricultural sector faces challenges owing to erratic precipitation and frequent droughts. The state's diverse population, including primitive tribes and various communities, relies significantly on agriculture for sustenance. Despite its rich biodiversity and mineral resources, Odisha faces environmental challenges. Forest cover loss attributed to logging, heavy reliance on forest resources, cropland expansion, and urbanization has resulted in significant damage to the forest cover in the state (Behera et al., 2018a). Thus, agroforestry interventions will help restoring the tree cover resources and improve livelihood and food security.

3 Data used

3.1 Satellite data

Sentinel-2 optical satellite remote sensing data are used in this study to generate land use land cover (LULC) map. Sentinel-2

carries an optical instrument capturing the Earth's surface in 13 spectral bands, categorised into four, six, and three bands with spatial resolutions of 10, 20, and 60 m, respectively. The cloud-free Sentinel-2 Level-1C (S2-L1C) multispectral images for May 2020 (Zaid), October 2020 (Kharif), and January 2021 (Rabi) were acquired from the Sentinel hub, providing radiometrically and geometrically corrected orthorectified Top-Of-Atmosphere (TOA) reflectance data. The visible and near-infrared bands with 10 m spatial resolution for the pre-monsoon, monsoon, and post-monsoon seasons (Zaid, Kharif, and Rabi seasons, respectively) were accessed for subsequent analysis.

The ALOS – PALSAR Digital Elevation model (DEM) with a spatial resolution of 12.5 m was used to generate the slope map (Table 1). The soil resource database of the National Bureau of Soil Survey and Land Use Planning (NBSS and LUP) was used as the base soil layer, which included various soil physical and nutrient parameters (Supplementary Figure S1). NBSS-LUP provides soil information at the regional level in India, generated through intensive ground surveys, LULC, and topographic variables, with the aid of Land Resource Inventory (LRI) technology (Supplementary Figures S1b–f).

The climate data were taken from the Worldclim database (www.worldclim.org accessed on 20 January 2021). WorldClim data were interpolated (thin-plate splines method) gridded weather data from approximately 60,000 weather stations across the globe, available at 30 arcsec (~1 km) resolution. Elevation, distance to the coast, and satellite-derived variables, maximum and minimum land surface temperature and cloud cover (derived Moderate Resolution Imaging Spectroradiometer; MODIS imagery)

were used as covariates in interpolation (Fick and Hijmans, 2021; Fick and Hijmans, 2017). Despite fitting a single model for the entire globe, each region was fitted with a separate model to improve accuracy and align it with the ground conditions. The minimum, maximum, and mean temperatures for the current years (1970–2000) were used in the present analysis (Supplementary Figures S2a–c).

The high-resolution (0.05°) Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) precipitation data was employed, wherein the annual precipitation was considered (Supplementary Figure S2). With an innovative interpolation technique, the CHIRPS data are generated based on the duration of Global Cloud cover, *in-situ* from gauged stations, and Cold Cloud Duration (CCD)-based satellite precipitation estimates from 1981 to the present. Initially, it produces preliminary information on precipitation with a 2-day latency and a final product with a 3-week latency (Funk et al., 2015).

Socioeconomic variables included proximity factors, such as distance to settlement (built-up), roads, waterbodies, forests, and croplands (Supplementary Figure S3). The Euclidean distance tool of the ArcGIS software was used to create the proximity layers. The data on settlement, roads, waterbodies, forests, and croplands used in the analysis were extracted from the LULC map.

3.2 Ground data

Ground geolocation data (latitude and longitude) were collected using a handheld geolocation instrument in 2020 for crop types and other LULC features. A total of 1888 points were collected from the ground using sites selected from high-resolution Google Earth imagery and multi-temporal (seasonal) Sentinel-2 for single-, double-, triple-crop, built-up, waterbody, forest, grassland, shrubland, fallow land, Wasteland, and Mangroves (Figure 2). The reference data were spatially distributed in the study area to confirm appropriate representation and heterogeneity. Most of the sample locations for dense forests were identified using high-resolution Google Earth imagery.

The reference data for agroforestry intervention included wadi (agro-horti-forestry), bund and boundary plantations, and home gardens. The agroforestry field data of 200 samples included the species information and geolocation of single (142) and mixed (58) species from the Belpada block (Figure 3a). Additionally, 75 agroforestry data points were collected from the Nuapada block (Figure 3b).

4 Methodology

4.1 Land use land cover (LULC) mapping

The RF and support vector machine (SVM) ML algorithms were applied for LULC mapping. RF is a supervised ensemble learning method that combines multiple decision trees (Breiman, 2002). RF identifies the relative importance of each determinant variable, achieving higher accuracy with larger datasets (Cutler et al., 2007; Zhou et al., 2016). Typically, 2/3 of the original dataset is used in a bootstrap sample, while the remaining 1/3, known as out-of-bag (OOB) data, is used to evaluate variable importance (Rodriguez-

Galiano et al., 2012). Model accuracy is enhanced by tuning two hyperparameters: the number of variables for node splitting (mtry) and the number of trees (ntree), with ntree set to 1,000 to minimize root mean square errors (RMSE) and ensure no error increase (Lawrence et al., 2006). The square root of the number of layers was used to determine mtry.

The SVM is popular for handling both continuous and categorical variables, with its performance largely dependent on the kernel function used. Common kernels include linear, Gaussian, and polynomial, with the kernel enhancing computational power for nonlinear data. The algorithm constructs a hyperplane in a new hyperspace to minimize error and model complexity (Vapnik, 1999). While efficient and capable of handling outliers, SVM can be prone to overfitting (Camps-Valls et al., 2006). This study applied a radial basis kernel, often used in image classification, and tuned the SVM model using cost and gamma parameters. The best model had zero epsilon and a cost value of 512, using 400 support vectors for image classification. The LULC with cropping intensity maps were developed using the Google Earth Engine (GEE) platform. These classified maps were utilized for prescribing agroforestry interventions.

4.2 Agroforestry suitability mapping

The ground data were collected from Belpada and Nuapada on various agroforestry systems, i.e., wadi (agro-horti-forestry), bund and boundary plantation, and home gardens. The previous trained model using the RF model (Singh et al., 2022) and validated in Belpada was used in the current study (Table 2). The pre-trained MCDM model indicated the dominant importance of proximity variables (cropland and road), followed by moderate importance of distance to settlement, temperature, and soil depth. On the contrary, lower importance was observed for remaining variables. The importance values were used to estimate the relative weight values, which were employed in MCDM analysis using the spatial layers. Following the input variables used in the previous study, all the 15 variables for entire Odisha state were analyzed. The process involves classifying and transforming variables into a fuzzy scale, varies between 0 and 1. Different fuzzy functions are used to convert variables based on their importance to agroforestry (e.g., a sigmoidal decreasing for slope, monotonically increasing linear for temperature). The agroforestry suitability map of Odisha was generated using the weights given in Table 2. The generated agroforestry suitability map was then validated using the *in-situ* data points collected in Nuapada. Also, model performance was evaluated using Receiver Operating Characteristic (ROC) analysis, from which sensitivity, specificity, and the optimal classification threshold were derived. Further, the agroforestry intervention maps were produced using the agroforestry suitability and LULC maps, following the criteria proposed by Singh et al. (2022). The bund plantation is proposed in double cropping agricultural lands that doesn't hinder the productive double cropping lands. Bund plantations and intercropping are prescribed in single cropping agricultural lands depending. The home gardens are prescribed in and around built-up areas, wherein block plantations in permanent fallow and waste lands.

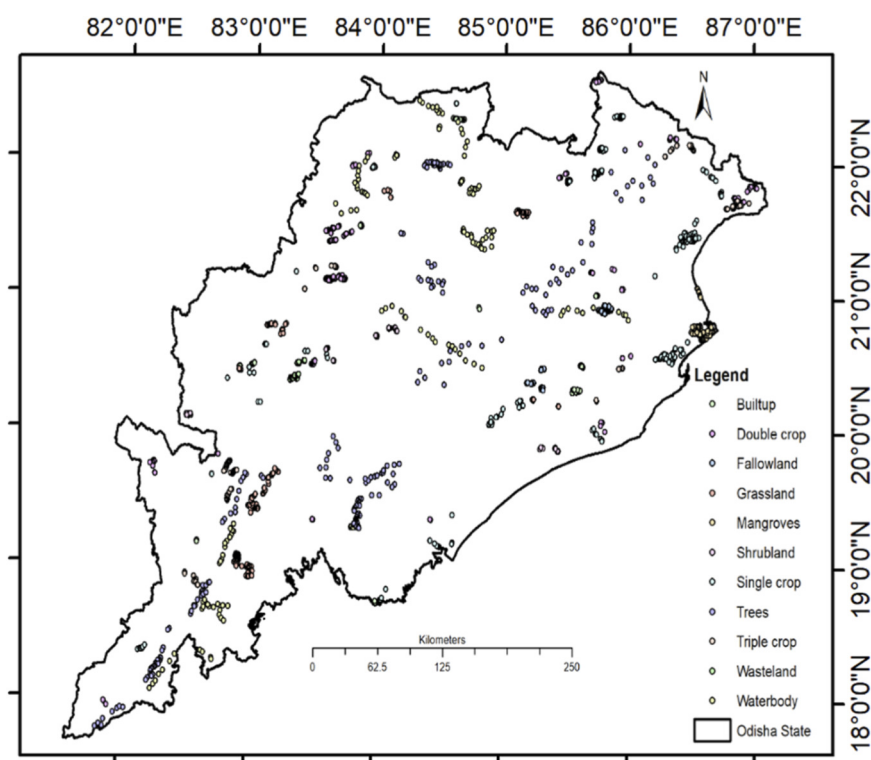


FIGURE 2
Reference data collected for LULC and crop intensity mapping.

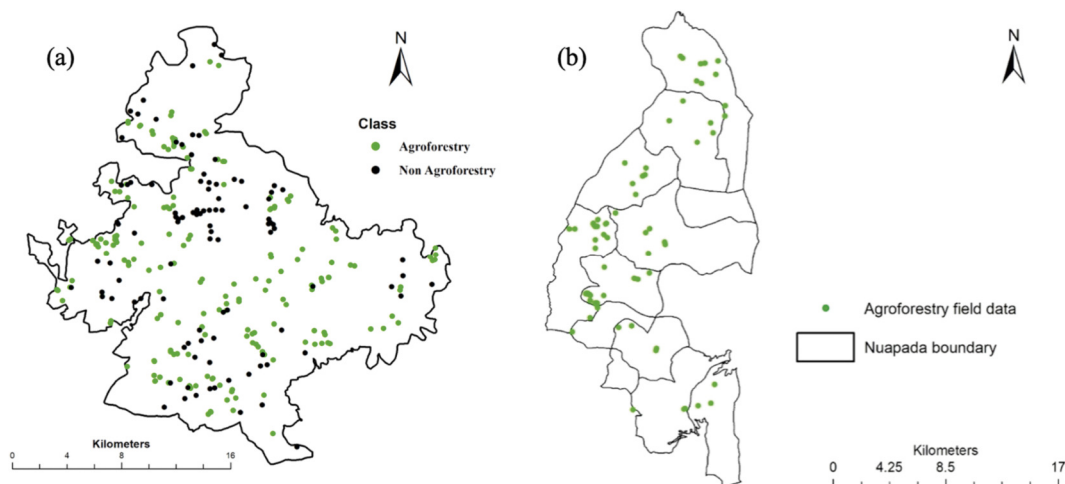


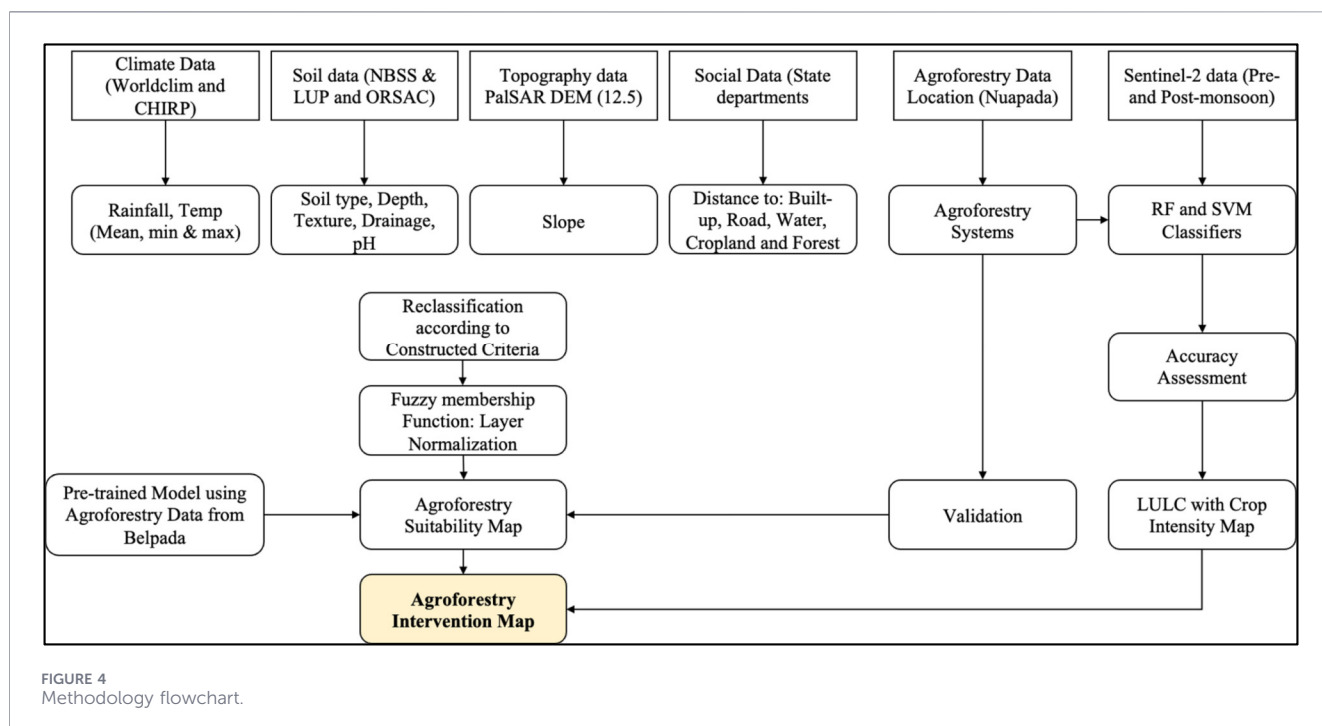
FIGURE 3
Ground data points of existing agroforestry patches collected in (a) Belpada and (b) Nuapada blocks, Odisha.

The overall data processing methodology is shown in Figure 4.

4.3 Agroforestry WebGIS application development

A WebGIS application developed in the current study consisted of a three-tier client-server architecture: (i) the client-side includes a

web browser, (ii) server-side consists of a web server, and (iii) a database linked by middleware. The application is designed as a group of services supplied by distributed servers, wherein a client may access these different services on servers and perform queries. The Internet Map Server (IMS) makes the GIS data available to end-user web browsers through the internet. An application script was integrated with HTML to show the contents on a client's computer.



All the spatial servers for maps are linked together and communicate with a web browser. Web server collects user requests from web browsers and displays the available results from the GIS spatial server to the web browser and subsequently to the clients. Users can access the data portal by utilizing the server's URL and sent to the client through HTTP.

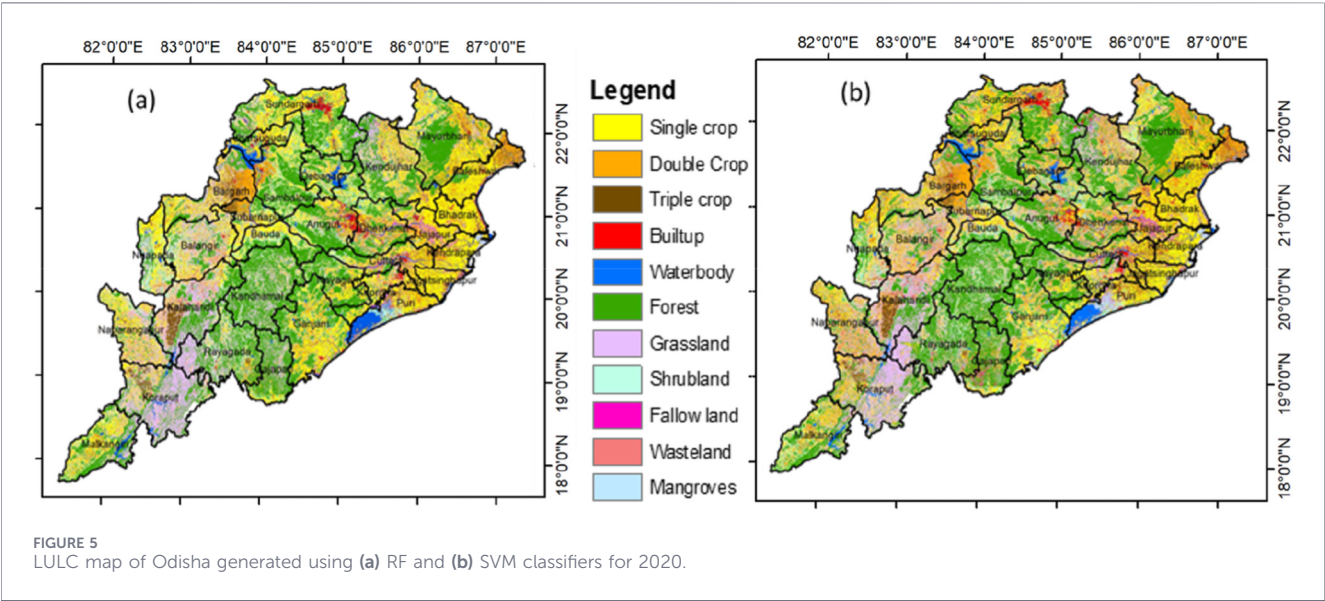
Two basic map servers were used in the current study, where the WFS displays vector data, and the WMS returns raster data or images. The open-source GeoServer is used here for sharing geospatial data. The developed platform contains multiple tools that are categorized into navigation, legend, search, and layer management. Features on the map can be identified using the map identify tool, while the measuring tool is added to measure distance (length) and area. Results of map query or area of interest can be printed along with the legend. The map can be produced and exported in various file formats such as PNG, JPEG, GIF, or PDF. The quick zoom tool allows user-defined region-specific zooming for closer view. The application included a query option, wherein the users can query using the non-spatial attributes through a small form/fields. Clicking the "Search by Value" will initiate a pop-up window listing the attribute table matching the search criteria, subsequent zooming, and highlighting the map.

5 Results

5.1 Land use land cover (LULC) classification and crop intensity

The LULC map of Odisha was generated using 1,524 training data points and validated using 364 points, randomly selected from the total 1888 reference data points (Figure 5). The RF and SVM classifiers applied to the multi-temporal Sentinel-2 data

demonstrated good accuracy, wherein the Overall Accuracy (OA) and kappa coefficients were 94.78% and 0.94, respectively, for RF, and 93.68% and 0.93, respectively, for SVM (Tables 3, 4). The RF-based classification demonstrated marginally higher accuracy than SVM (User's Accuracy UA: 98.34% for RF and 96.21% for SVM) for single crops. The RF and SVM achieved similar UA values for trees, water, fallow land, and mangroves. The higher accuracy in SVM indicates higher margin gaps between separating hyperplanes (positive and negative hyperplanes) for spectrally different classes (e.g., forest and waterbody) than lower margin gaps for spectrally similar classes, such as various crop types and forests. Most croplands were found in coastal belts and western districts. Out of the total cropland (~32.21%), single, double, and triple crops accounted for 22.34%, 6.8%, and 2.12% of the area, respectively (Table 5). The generated LULC map for Odisha shows that the majority of cropland is in the coastal belt and western districts, while forests dominate the central region. The classified maps exhibited a predominance of single-cropped areas (22.34%), followed by double-cropping areas (6.8%) and triple-cropping areas (2.12%). The highest concentrations of single-cropped areas were identified in Mayurbhanj (1.51%), Sundargarh (1.34%), and Balangir (1.30%) districts, and the lowest in Gajapati district (0.2%). The majority of double-cropped areas were identified in the Bargarh (0.84%), Baleshwar (0.58%), and Jajpur (0.32%) districts, wherein the least was in the Nayagarh district (0.04%). The Kalahandi district has the highest triple-cropped area (0.37%), and the Kandhamal district has the smallest area (0.01%). Forest occupies 33.46% of the total area, and the Kandhamal district has the highest forest cover (3.18%). Fallow land accounted for 0.95% of the total area. The built-up area accounts for 2.4% of the total area, and water bodies, shrublands, grasslands, wastelands, and mangroves occupy the remaining 36%.



5.2 Scaling-up of suitable agroforestry interventions for Odisha

The agroforestry site suitability map was generated by applying the weights proposed by Singh et al. (2022) for entire Odisha state, is

TABLE 2 RF estimated weights for different variables (following the weight values suggested by Singh et al., 2022).

Sl. No.	Factors	Variable importance	Relative weight
1	Soil type	1.06	0.01
2	Soil depth	3.41	0.05
3	Soil texture	2.27	0.03
4	Soil drainage capacity	0.78	0.01
5	Soil hpH	2.38	0.03
6	Slope	0.85	0.01
7	Mean temperature	2.74	0.04
8	Minimum temperature	4.36	0.06
9	Maximum temperature	3.14	0.04
10	Precipitation	0.73	0.01
11	Distance from settlement	6.04	0.08
12	Distance from road	21.29	0.28
13	Distance from water	1.57	0.02
14	Distance from cropland	23.05	0.31
15	Distance from forest	1.03	0.01

shown in Figure 6. The agroforestry suitability map was classified into four groups: low, moderate, high, and very high suitability, based on an equal interval value of 0.25. The agroforestry suitability map was validated using the *in-situ* data points collected from another landscape, i.e., Nuapada block. The agroforestry data points from the Nuapada district were overlaid on the agroforestry suitability map, which indicated a high average value (>0.87 with a value range from 0.71 to 0.95). The high average suitability validated through an independent landscape determines the applicability of the weights proposed by Singh et al. (2022). Further, the agroforestry suitability map was overlaid on the LULC map (agriculture, settlement, fallow land, and waste lands) to generate the intervention map.

The performance of the agroforestry model was examined using Receiver Operating Characteristic (ROC) analysis. The estimated Area Under the Curve (AUC) value as 0.89, indicating very good model performance in site suitability analysis (Supplementary Figure S4). The ROC curve lies well above the 1:1 or identity line, demonstrating that the model can effectively distinguish suitable agroforestry locations from non-suitable areas. This high AUC value confirms the robustness and reliability of the RF-based weight prediction for agroforestry site identification. The inclusion of sensitivity and specificity metrics further strengthens the reliability of the suitability classification.

5.3 Generating suitability maps for various agroforestry interventions

5.3.1 Bund and boundary plantation and intercropping

Double-cropping system: Double-cropped land, mainly grows paddy in the monsoon/Kharif season and pulses or partially grown second paddy crop in the Rabi season. The double-cropping agricultural lands (1,062,519 ha) were prescribed for bund and boundary plantations (Figure 7a). The double-cropped area superimposed on the agroforestry suitability map showed very high suitability for more than 94% (1,007,800 ha) of the

TABLE 3 Classification error matrix for validation data generated using RF classifier.

Classes	Single crop	Double crop	Triple crop	Built-up	Water	Trees	Grassland	Shrub land	Fallow land	Wasteland	Mangroves	Total	UA
Single crop	54	0	0	0	0	0	1	0	0	0	0	55	98
Double crop	3	38	0	0	0	0	0	0	0	0	0	41	93
Triple crop	0	5	18	0	0	0	0	0	0	0	0	23	78
Built up	0	0	0	18	0	0	0	0	0	0	0	18	100
Water	0	0	0	0	29	0	0	0	0	0	0	29	100
Trees	0	0	0	0	0	43	0	1	0	0	0	44	98
Grassland	2	1	0	0	0	0	35	2	0	0	0	40	88
Shrubland	1	0	0	0	0	0	0	35	0	0	0	36	97
Fallowland	0	0	0	0	0	0	0	0	25	0	0	25	100
Wasteland	1	0	0	1	0	0	1	0	0	26	0	29	90
Mangroves	0	0	0	0	0	0	0	0	0	0	24	24	100
Total	61	44	18	19	29	43	37	38	25	26	24	364	-
PA	88.5	86.4	100.0	94.7	100.0	100.0	94.6	92.1	100.0	100.0	100.0	-	-
Overall accuracy = 94.78						Kappa = 0.94							

TABLE 4 Classification error matrix for validation data generated using SVM classifier.

Classes	Single crop	Double crop	Triple crop	Built-up	Water	Trees	Grass land	Shrub-land	Fallow land	Waste land	Mangroves	Total	UA
Single crop	53	0	0	0	0	0	2	0	0	0	0	55	96
Double crop	3	38	0	0	0	0	0	0	0	0	0	41	93
Triple	0	4	19	0	0	0	0	0	0	0	0	23	83
Built up	0	0	0	17	0	0	0	0	0	1	0	18	94
Water	0	0	0	0	29	0	0	0	0	0	0	29	100
Trees	0	0	0	0	0	43	0	1	0	0	0	44	98
Grassland	4	0	0	0	0	1	32	0	0	3	0	40	80
Shrubland	0	0	0	0	0	1	2	33	0	0	0	36	92
Fallow land	0	0	0	0	0	0	0	0	25	0	0	25	100
Wasteland	1	0	0	0	0	0	0	0	0	28	0	29	97
Mangroves	0	0	0	0	0	0	0	0	0	0	24	24	100
Total	61	42	19	17	29	45	36	34	25	32	24	364	-
PA	87	90	100	100	100	96	89	97	100	88	100	-	-
Overall accuracy = 93.68					Kappa = 0.93								

TABLE 5 Area statistics of the classified map generated using RF model.

Class	Class area (km ²)	Class area (%)
Single crop	34663.25	22.34
Double crop	10554.95	6.80
Triple crop	3293.53	2.12
Built up	3820.70	2.46
Waterbody	5360.51	3.45
Forest	53160.15	33.46
Grassland	23042.65	14.85
Shrubland	16060.57	11.15
Fallow land	1474.60	0.95
Wasteland	2776.75	1.79
Mangroves	969.31	0.62

total double-cropland area, followed by high suitability for 44,407 ha (4%) (Table 6). Only 0.97% of the land was classified as moderately or less suitable. The highest suitability was mainly observed for agricultural lands along the stream network, coastal regions, and reservoirs, such as the Hirakud Dam. The maximum double-croplands are identified in northeastern districts, including Mayurbhanj, Baleshwar, Bhadrak, Jajapur, and western districts like Bargarh, Sambalpur, and Subranapur. The highest suitable areas for bund and boundary plantation are found in Bargarh (130,500 ha) and Mayurbhanj (132,100 ha), and the least in Nayagarh (7,300 ha) and Debagarh (8,200 ha).

Single cropping system: Paddy is the most dominant single cropping practice cultivated in the monsoon (Kharif) season. It remained fallow in the Rabi and Zaid seasons, primarily due to a lack of irrigation facilities or depletion of residual moisture for long-duration rice varieties. Such land is considered suitable for bund, boundary plantation, and intercropping (Figure 7b). The total area suitable for bund and boundary plantations with conditional intercropping is 3,493,326 ha, of which ~94% of the total area falls into the very high suitability class, ~5% falls under the high

suitability class, and only 0.75% falls under the moderate to the less appropriate class. The highest proportion of single-crop land was observed in the coastal districts of Bhadrak, Kendrapara, and Jagatsinghpur. In terms of suitability, the highest proportionate of suitable areas for intercropping with bund and boundary plantations is observed in Ganjam district, and the least in Rayagada, Kandhamal, and Gajapati. Moreover, the majority suitable areas were estimated in the southwestern Naharangapur district.

Home Gardens: A home garden, also known as a backyard plantation, is the most adopted agroforestry model and is a common practice in Odisha compared to other approaches. Nearly 384,817 ha (96.29%) of the total settlement area was identified as suitable for home gardens, whereas only 3.71% were identified as less and moderately suitable (Figure 7c). The maximum land is ideal for home gardens in the Sundargarh (52,200 ha) and the lowest in the Kandhamal district (1,369 ha). Dominant home garden interventions are prescribed in several other districts, such as Anugul, Dhenkanal, Jajapur, Cuttack, Bhadrak, Puri, Khordha, and Kendrapara.

Block/Bulk Plantation: The block/bulk and bamboo plantations are primarily prescribed in the permanent fallow and wastelands (Figures 7d,e). The total estimated wasteland of 148,500 ha and very high suitability projected in ~93.01% (138,131 ha) area, followed by high suitability in 3.29% (4,886 ha) area, whereas only 3.7% area showed least suitable. Similarly, the total area of permanent fallow of 120,500 ha and ~90.58% (109,186 ha) area estimated very high suitable, class, followed by high appropriate in 6.58% (7,927 ha) area, whereas only 2.84% area found least suitable. The majority of the bulk plantation is identified in the Balangir, Kalahandi, and Jajpur districts, with the lowest in the Kandhamal district.

5.4 Agroforestry suitability WebGIS portal

WebGIS platform can function on multiple operating systems such as Windows, Linux, or standard mobile operating systems like Android, iOS, and Windows. The users can visualize the data, run simple query analyses, and display the results (Figure 8). The colour palette (legend) on the left side of the page allows users to comprehend the agroforestry index value (Low to high). The WebGIS portal uses the Google map view and satellite view as the base layers, wherein the users can choose the desired base layer.

TABLE 6 Agroforestry suitability statistics under the various agroforestry interventions.

Classes	Interventions	LULC area (km ²)	Class area (km ²)				Class area (%)			
			Low	Mod	High	Very high	Low	Mod	High	Very high
Double crop:	Bund & boundary plantation	10625.19	101.61	0.57	444.07	10078.93	0.96	0.01	4.18	94.86
Single crop:	Intercropping and bund & boundary plantation	34933.26	259.54	0.97	1735.15	32937.60	0.74	0.01	4.97	94.29
Settlement	Homegarden	3848.17	186.54	0.56	112.08	3548.99	4.85	0.01	2.91	92.23
Fallow land	Bulk/block plantation	1485.29	54.98	0.12	48.86	1381.31	3.70	0.01	3.29	93.01
Wasteland	Bulk/block plantation	1205.48	34.22	0.13	79.27	1091.86	2.84	0.01	6.58	90.58

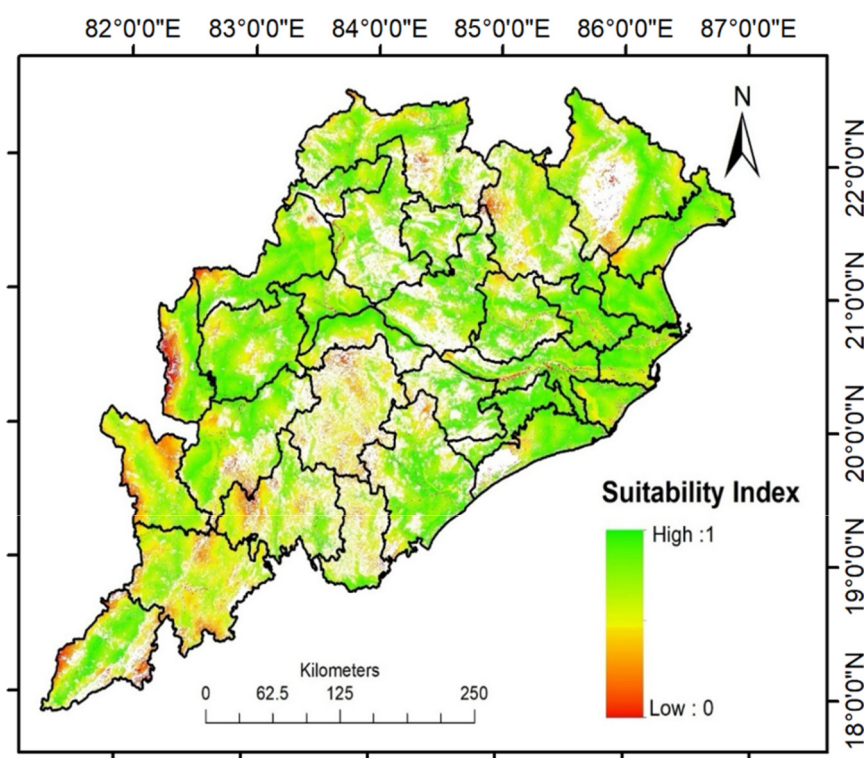


FIGURE 6
Agroforestry suitability of Odisha.

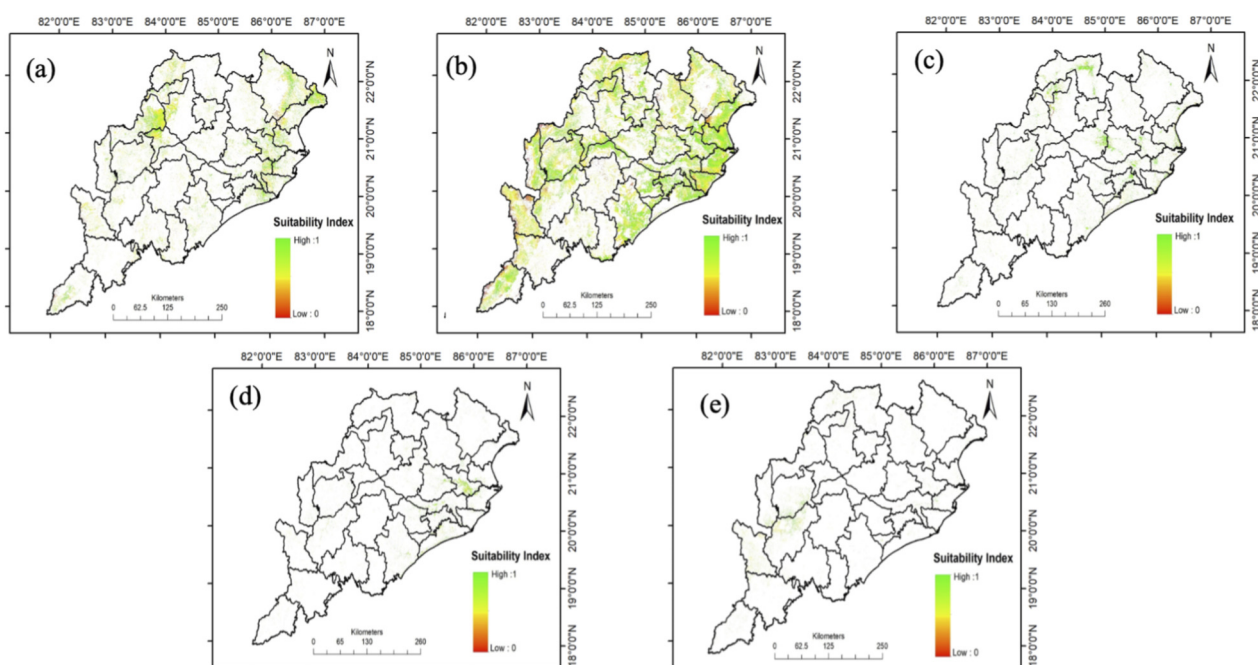


FIGURE 7
Agroforestry suitability for (a) bund and boundary plantation in double cropping land, (b) bund plantation, boundary, and intercropping in single cropping land, (c) home gardens, (d) bund and block/bulk plantations in fallow land and (e) block/bulk plantations (Wasteland).

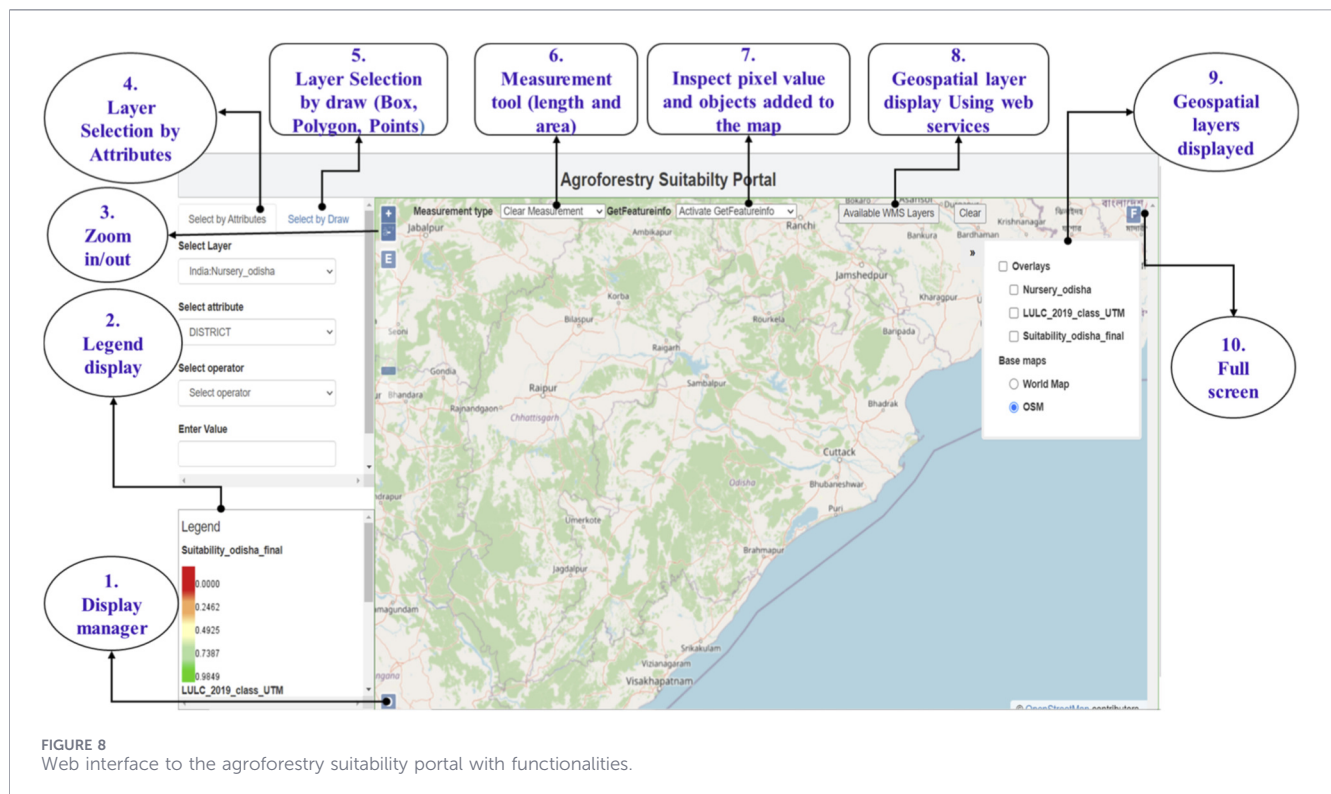


FIGURE 8
Web interface to the agroforestry suitability portal with functionalities.

The various important components of the agroforestry application are listed below:

- i. Display manager: This tab regulates the overall display at any part of the platform.
- ii. Legend display: This tab displays the various legends of the selected data.
- iii. Zoom in/out: This option allows users to zoom in/out for closer and broader layer view.
- iv. Layers Selection by attributes: This allows for query and respective layer selection.
- v. Selection by draw (Box, Polygon, Points): It allows to draw the desired area for inquiry or define the area of interest (AOI).
- vi. Measurement tool (length and area): It allows measures such as area and length.
- vii. Inspect pixel values and objects added to the map: It helps inspect the pixel information (e.g., agroforestry suitability values) from raster and vector layers.
- viii. Geospatial layer displays: It shows the available data layers in the platform.
- ix. Geospatial layers displayed: It provides various base layers such as Google street view, satellite view, etc.

The output maps generated in the study, such as LULC, agroforestry suitability and intervention maps, were uploaded to the platform (Figure 9). The vector data as state, district, and block administration boundaries were added. A user can use the inquiry tool (add a point location) or select the administrative area (village/block) to identify the suitable agroforestry intervention and suitability index value. In addition, the

nursery (geolocation and planting material availability) in Odisha state was added to help farmers identify and navigate the nearest nursery. As quality planting material is challenging for farmers, this platform will connect to the Odisha nursery database. Based on the user's location, it will list neighbouring nurseries within a 2–10 km radius, allowing farmers to receive the best quality planting material.

6 Discussion

The multi-temporal seasonal (pre-monsoon, monsoon, and post-monsoon) Sentinel-2 imagery at 10 m spatial resolution yielded high accuracy in mapping LULC and cropping intensity. Both the machine learning algorithms (RF and SVM) produced high accuracy, wherein the RF demonstrated a better classification accuracy (OA: 95.78% and kappa 0.94) than SVM (OA: 93.68% and 0.93), substantiating the accuracy reported in previous studies (Belgiu and Csillik, 2018; Defourny et al., 2019; Das and Pandey, 2019). The Sentinel-2 time-series data were used to identify temporal trends for agricultural practices that were sufficiently stable in relevance to seasonal and inter-annual variations (Singh et al., 2021a). The high temporal resolution (5 days) of Sentinel-2 data captured the distinct trajectories and provides signature for cropping intensity identification (Ghosh et al., 2017). The LULC maps generated by Behera et al. (2018a) validate the LULC dominance observed in the current study.

The generated LULC and crop intensity map identified most of the cropland in the coastal belt and western districts, whereas forests dominate the central region. Crop intensity dynamics could be affected by various factors, such as the seasonal rainfall,

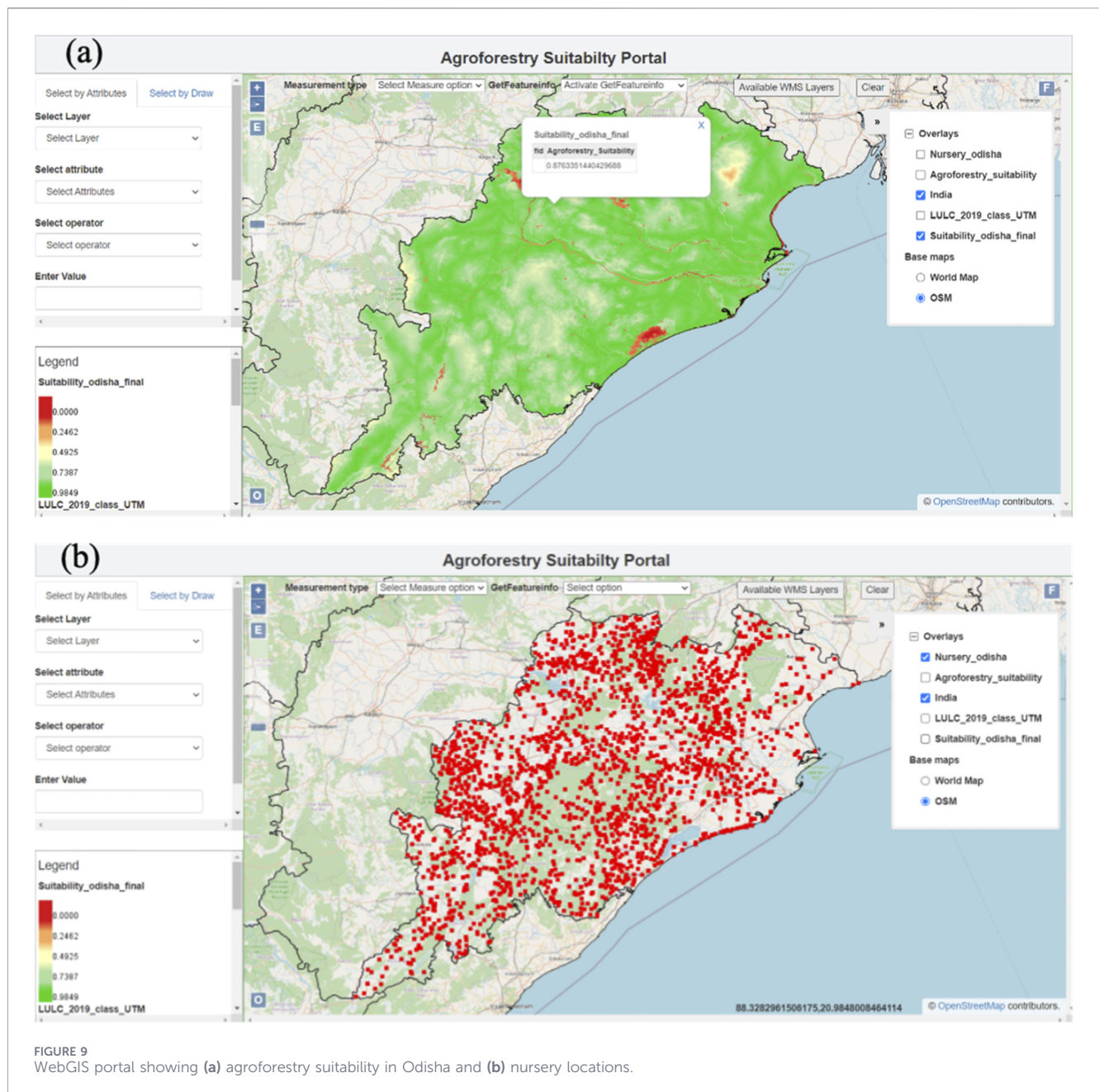


FIGURE 9
WebGIS portal showing (a) agroforestry suitability in Odisha and (b) nursery locations.

availability of supplemental irrigation during the Rabi and Zaid seasons, and other social factors (e.g., stray cattle grazing). In the coastal region of Odisha, the double crop concentration is higher due to fertile alluvial soil with suitable monsoon precipitation, providing sufficient residual soil moisture (after the Kharif crop harvest) to be utilized for the additional crop during the Rabi season. The study by [Chandna and Mondal \(2020\)](#) demonstrated a similar cropping pattern in different parts of Odisha. The western parts of Odisha received relatively less precipitation, resulting in inadequate soil moisture for the second crop and predominantly rely on irrigation. Thus, most of the land remained fallow during the Rabi and Zaid seasons. Tripple cropping lands are less abundant in Odisha. Kalahandi has the highest triple-cropped area owing to multiple irrigation projects aimed at enhancing food security and

improving livelihoods ([Yasmin and Srinivas, 2020](#)). The forest cover occupies around 33.46% of the total land cover in Odisha, and the Kandhamal district had the highest forest cover. The Forest Survey of India (FSI) reported similar results (33.50% of the state's geographical area), with an increase of 537 sq. km, 0.3% of the state's geographical location from 2017 to 2019.

The current study applied a pre-trained (integrated RF and fuzzy-MCE) agroforestry suitability model developed using extensive used field data in this region, whereas most of the previous studies utilized perspective-based analysis for agroforestry suitability. Socioeconomic (proximity) variables were identified more important, wherein the maximum value was observed for distance to cropland (31%) and road (28%), followed by the distance to settlement (8%). The combined

proximity variables contributed 70% of the total weight. In comparison, lower weights were estimated for climate, topography and soil parameters, in the agroforestry suitability assessment. The higher importance of the proximity variables can be attributed to accessibility and connectivity, and local people's preference for selecting suitable areas for agroforestry interventions, which provides easy access, regular monitoring and better management. The lower importance of the soil variables showed that the soil types were primarily uniform and had significantly less variability in the regions and the value being in suitable ranges. Proximity to the waterbody indicated lower importance. It has been substantiated by field observation, which revealed that several micro-irrigation systems were installed to ensure sapling survival during dry summers. The water-filled pipe structure was installed around plants/saplings to supplement the plant's water requirement for 1–2 weeks for their sustainability in the summer.

More than 90% of the cultivable lands, home-gardens around houses, permanent fallow land, and waste land are found highly suitable, denotes the potential for agroforestry interventions in Odisha. [Doddabasawa et al. \(2019\)](#) evaluated agroforestry interventions in six districts of Karnataka, India. They reported six agroforestry systems, wherein the bund plantation was declared the dominant system (43.06%), followed by the boundary plantation (19.44%) practiced in this region. They reported that farmers preferred bund and boundary plantations over other interventions. [Ahmad et al. \(2019\)](#) conducted a national assessment of agroforestry suitability in India, and identified 46% of India's agricultural land as suitable out of a total of 52%. Agricultural lands in tropical and subtropical climate zones, including the current study site, are estimated to be highly suitable for agroforestry interventions. In addition to identifying agroforestry suitability, the spatial patterns observed in this study have important implications for carbon sequestration potential. Previous studies have demonstrated that agroforestry systems can store substantial amounts of carbon in both above- and below-ground biomass, depending on species composition, management practices, and site conditions. Areas classified as highly suitable in this study are therefore likely to support greater biomass accumulation and, consequently, higher potential carbon stocks. Previous studies in the Belpada Block of Balangir, Odisha, reported a potential carbon stock of 15 Mg/ha over 5 years. Although, carbon stocks were not directly quantified in this study, linking suitability classes with literature-based estimates provides a useful proxy for identifying priority zones for climate-smart land-use planning and carbon mitigation strategies.

The relative weights estimated for a region (i.e., Belpada) were validated using field observed data from another landscape as Nuapada and further extrapolated at the state level. The high accuracy of the agroforestry suitability in Nuapada demonstrates the scalability of our previously trained model in Belpada, also verified by the ROC curve and AUC value (0.89). The approach demonstrated the scalability, and provides robust basis of using a pre-trained model with modifications in similar climate zones or landscapes, especially in agriculture-dominated regions in the tropical climate zones.

Moreover, future studies in the study area may include well-sampled field interventions all over the state in a well-dispersed manner are currently limited in the present study. Future studies may access suitable data from the horticulture department, with at least 200–300 samples for each type of intervention or major species for the entire state will improve the current modeling accuracy and allow species-wise analysis. The current method relies heavily on existing agroforestry interventions and local practices, which may be unavailable for many regions or costly to collect. However, the study utilizes existing agroforestry data, which provides an accurate assessment of suitability compared to approaches that rely on *ad hoc* or perspective-based weights. The generated output can help planners implement suitable agroforestry systems. The generated data working as a baseline layer could be helpful in the stakeholder's consultation with local people or beneficiaries as the next step to implementation. The spatially explicit data and information will help develop suitable agroforestry policies, as well as effective agricultural and water resource management, in location-specific conditions.

This WebGIS platform employed spatial information to display suitable areas for agroforestry and appropriate interventions in Odisha. The platform has potential to host multiple layers, including raster and vector formats. The on-screen measuring tool for measuring area and length. It is beneficial for area marking and extracting agroforestry suitability index and prescribed suitable intervention for any region. The nursery database was included to search the nearby nursery address and seller's contact information so the user could connect to the nursery.

While this study provides important insights into agroforestry suitability and phenological responses under current conditions, several limitations remain for future research and improvement potential. First, a detailed cost–benefit analysis for implementing agroforestry interventions is beyond the present scope but will be essential to assess financial viability and support large-scale adoption. Second, assessing climate change impact studies, integrating Shared Socioeconomic Pathways (SSPs) scenarios to evaluate how projected shifts in hydroclimatic settings may influence agroforestry suitability and predicting the climate resilience. The suitability maps can be generated for 10- or 20-years interval SSP scenarios and assessing the changes site suitability. Further, such changes will be more important for species specific suitability assessment. Third, tracking the adaptation at periodic intervals and success rate by capturing year-wise mortality, climate resilience, ecological and economic benefits. In addition, linking the adaptation with existing government and non-government scheme could expand the adaptation rate and reach individual interested farmer. Recent studies emphasise the importance of these factors in shaping adoption decisions ([Tranchina et al., 2024](#); [Panwar et al., 2023](#)). Accordingly, suitability mapping alone is insufficient to drive implementation; its effectiveness depends on integration with enabling policy instruments (e.g., SMAF, MGNREGA, RKVY, MIDH, GROW). Together, these extensions will strengthen the applicability, robustness, and climate relevance of agroforestry-based land-use planning. Finally, translating suitability into practice requires integration with socio-economic realities, including adoption barriers such as market access, policy uncertainty, and land tenure constraints. Moreover,

sensitivity analyses across spatial units (e.g., inclusion/exclusion of districts) would improve the robustness of suitability assessments. In addition to several other benefits, agroforestry interventions, especially the multistrata systems promote and conserve species diversity, and develop seed banks compared to conventional agricultural and plantation practices (Nair et al., 2022). Further, diversification of tree composition through agroforestry systems enriches the soil fertility (Vera-Vélez et al., 2021). Thus, agroforestry interventions must include the diversity parameters into sustainable implementation at a local to regional level. For biodiversity assessment, functional diversity parameters, α (estimated through Shannon or Simpson indices to examine species richness) and β -diversity (Bray–Curtis dissimilarity or Jaccard index to measures difference in species composition between different communities or sites) can be analysed using the species occurrence data.

7 Conclusion

Sentinel-2 satellite data was utilized to analyse crop intensity and assess agroforestry suitability combining fuzzy logic and GIS techniques. A pre-trained model developed using the RF algorithm was employed for weight estimation, while fuzzy theory helped translate numerical data into categories important for agroforestry suitability. Socioeconomic factors, particularly proximity were more effective in identifying suitable areas for agroforestry interventions in a sub-humid tropical climate. The model validation using a data from an independent region satisfies the scalability of the agroforestry suitability model. Integrating suitability map with LULC maps through criteria-based approach effectively identified the suitable interventions like bund and boundary plantations, intercropping, and block plantations. The developed model can be tested to other similar regions, requiring minor adjustments to the indicator lists and model. Landscape-level agroforestry suitability maps are useful in planning and implementation of activities under MGNREGA, GIM, RKVY, MIDH, and GROW in Odisha. The developed agroforestry WebGIS portal will help farmers choose suitable site-specific intervention plans for their location. The portal not only assists in identifying the right kind of agroforestry interventions but also provides complete information on integrated agroforestry systems, availability of quality planting material, and locations of the nearest nurseries. These state-level and district-level maps are helpful for the resource managers and policymakers for planning, improved decision-making, and implementation. Overall sustainable agroforestry practices will benefit reducing soil erosion, enhancing water retention, mitigating climate change, restoring ecosystems and biodiversity, improving food and nutrition security, and supporting economic development.

Data availability statement

The original contributions presented in the study are included in the article/[Supplementary Material](#), further inquiries can be directed to the corresponding author.

Author contributions

RS: Conceptualization, Data curation, Formal Analysis, Methodology, Software, Validation, Writing – original draft, Writing – review and editing, Investigation, Project administration. SG: Resources, Writing – review and editing, Conceptualization. PD: Conceptualization, Writing – review and editing, Methodology, Visualization. AJ: Data curation, Writing – review and editing. MB: Supervision, Writing – review and editing, Resources. CB: Supervision, Writing – review and editing, Project administration. SM: Visualization, Writing – review and editing, Software. VK: Writing – review and editing. AD: Writing – review and editing, Investigation, Resources. SK: Supervision, Writing – review and editing, Resources. SD: Resources, Supervision, Writing – review and editing.

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Conflict of interest

Author CB was employed by Global Green Growth Co.

The remaining author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/frsen.2026.1780218/full#supplementary-material>

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